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Diabetic Retinopathy Detection Using CNN

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ABSTRACT: Diabetes is one of the leading fatal disease globally, putting a huge burden on the global healthcare system. Early diagnosis of diabetes is hence, of utmost importance and could save many lives. However, current techniques to determine whether a person has diabetes or has the risk of developing are primarily reliant upon clinical biomarkers. In this article, we propose a novel deep learning architecture to predict if a person has diabetes or not from a photograph of his/her retina.

Using a relatively small-sized dataset, we develop a multi-stage convolutional neural network (CNN)-based model Dianet that can reach an accuracy level of over 84% on this task, and in doing so, successfully identifies the regions on the retina images that contribute to its decision-making process, as corroborated by the medical experts in the field. This is the first study that highlights the distinguishing capability of the retinal images for diabetes patients in the Qatari population to the best of our knowledge.

KEYWORDS: Convolutional Neural Network, Deep Learning, Diabetes, Machine Learning, Qatar, Qatar Bio bank(QBB), retina.

I. INTRODUCTION

Diabetes mellitus or diabetes is considered as a collection of metabolic conditions that can predominantly be described by hyperglycemia rising from the deficiency in insulin discharge [1]. The prolonged hyperglycemia of diabetes is correlated with long-term impairment and collapse of heart, kidneys, and micro vascular circulation of the retina [2]. Among the diabetic individuals in the USA, almost 30% of them have the tendency of growing diabetic retinopathy (DR), a common complication for diabetic patients which may lead to blindness.

Diabetes may adversely affect the vascular system of the retina causing structural change of it [2]. As the changes in vascular structure in retina can provide visual cues for diabetes, most of the clinical guidelines recommended annual retinal screen for the diabetic patients through retinal fundus images or dilated eye examinations. Alternatively, these retinal images could be used to detect diabetes as well, but it requires subjective judgment from the ophthalmologist, and it might be time consuming as well. The human oriented subjective judgment could be avoided if we could implement the automation of retinal image-based diabetes diagnosis in clinical setup. Such automation could alleviate the workload of the ophthalmologist as well as screen a large number of patients objectively within a short amount of time. There exist many studies, based on Qatar, for the diagnosis and the potential risk factors of diabetes. Shi and Abou-Samra showed that magnesium deficiency is a very common symptom in the Qatari diabetic cohort

II. LITERATURE SURVEY

[1] D. Mellitus, "Diagnosis and classification of diabetes mellitus," *Diabetes Care*, vol. 37, no. 1, pp. S81–S90, 2014. [Online]. Available: https://care.diabetesjournals.org/content/37/Supplement_1/S81 Diabetes is a group of metabolic diseases characterized by hyperglycemia resulting from defects in insulin secretion, insulin action, or both.

[2] E. S. Shin, C. M. Sorenson, and N. Sheibani, "Diabetes and retinal vascular dysfunction," *J. Ophthalmic Vis. Res.*, vol. 9, no. 3, pp. 362–373, Sep. 2014. we have determined the identity of the retinal vascular cells affected by hyperglycemia, and have delineated the cell autonomous impact of high glucose on function of these cells. We discuss some of the high glucose specific changes in retinal vascular cells and their contribution to retinal vascular dysfunction.

[3] X. Zhang, J. B. Saaddine, C.-F. Chou, M. F. Cotch, Y. J. Cheng, L. S. Geiss, E. W. Gregg, A. L. Albright, B. E. K. Klein, and R. Klein, "Prevalence of diabetic retinopathy in the United States, 2005-2008," *JAMA*, vol. 304, no. 6, pp.

649–656, Aug. 2010. Diabetic Retinopathy Is The leading cause of new cases of legal blindness among adults aged 20 to 74 years in the United States.1 Vision loss due to diabetic retinopathy occurs through a variety of mechanisms, including retinal detachment, preretinal or vitreous hemorrhage, associated nonvascular glaucoma, and macular edema or capillary nonperfusion.

[4] J. Yau, S. Rogers, and R. Kawasaki, “Global prevalence and major risk factors of diabetic retinopathy,” Diabetic retinopathy (DR) is the leading cause of blindness among working aged adults around the world (1). Despite the significance of this problem, and the rising prevalence of diabetes notably in emerging Asian countries such as India and China (2,3), there are few precise contemporary estimates of the worldwide prevalence of DR, particularly severe vision-threatening stages of the disease, including proliferative DR (PDR) and diabetic macular edema (DME).

III. EXISTING SYSTEM

There are many existing techniques used for diabetic retinopathy classification and found many limitations as well as complexity. Machine learning is a branch of Artificial Intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy. IBM has a rich history with machine learning. One of its own, Arthur Samuel, is credited for coming the term, “Machine learning” with his research around the game of checkers.

IV. PROPOSED SYSTEM

In this section, we discuss in detail the process involved in the collection, curation, and pre-processing of the dataset as it pertains to this work and the development of our proposed solution for the problem at hand. Our proposed approach uses two datasets to achieve state-of-the-art in detecting diabetes from retinal images. The larger of these datasets contains retinal images from patients with different stages of DR, while the other, smaller dataset, and contains retinal images from diabetic patients and a control group. We describe the smaller dataset first since it is more closely related to the goal of our work and is also one of the contributions of this paper.

BLOCK DIAGRAM

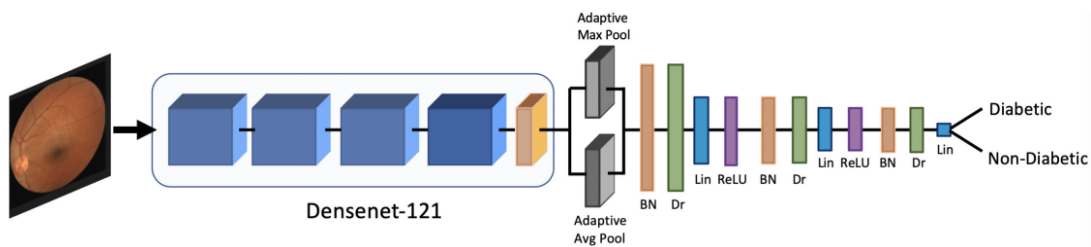


Figure 1: Block Diagram

The proposed architecture of DiaNet consists of a DenseNet-121 backbone and a few additional layers consisting of a pair of pooling layers followed by three composite layers each consisting of primarily a sequence of batch normalization (BN), dropout (Dr), linear (Lin), and a ReLU activation layer.

The final layer contains a single neuron indicating the predicted label (diabetic/non-diabetic). models that are much deeper than AlexNet or VGG, and differs from ResNet in the manner in which the feature maps from the previous layers are combined.

We used the 121-layer variant of Dense Net which consists of four dense blocks due to its superior performance. In spite of the network being 121-layer deep, over fitting was not an issue due to (i) the dense connections themselves acting as regularizer [32] and (ii) counter-intuitively, the network having less parameters compared to a non-dense CNN [32]. In ResNets, feature maps are combined downstream using the addition operation, which means feature maps are summed element-by-element along the channel (feature map) dimension, while in Dense Net; they are concatenated, along the same dimension.

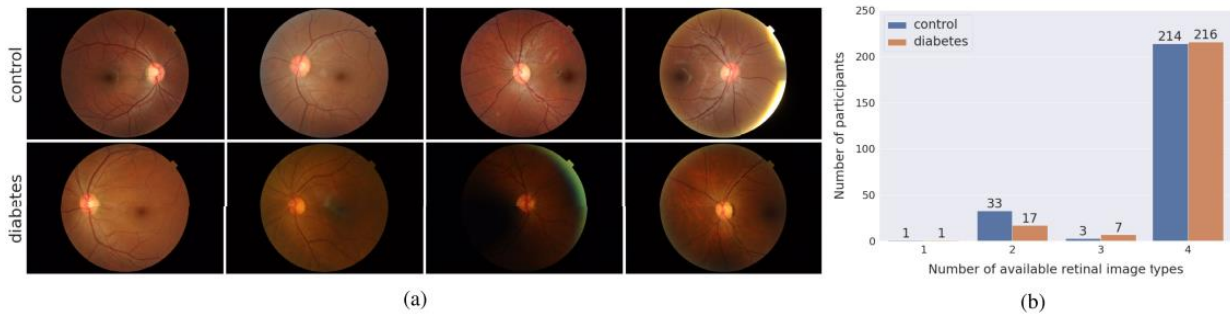


Figure 2: Data set

The diabetes group was free from self-reported diabetic status or HbA1c% >D 6.5. The control group was free from diabetes, obesity, and cardiovascular disease. All the subjects from the cohort were Qatari nationals. The cohort was evenly distributed based on male and female gender (i.e. 50% each) for both groups. Topcon TRC-NW6S retinal camera was used at QBB to capture the “microscopic” features of the optic nerve and macula from the participants. The details of the data collection protocol. A set of retinal images from the QBB dataset is shown in (a), while (b) shows the number of participants with each of the four types of image availability configuration: (left, right) × (macula-centered, disc-centered). Most participants had both macula-centered and disc-centered images from both eyes.

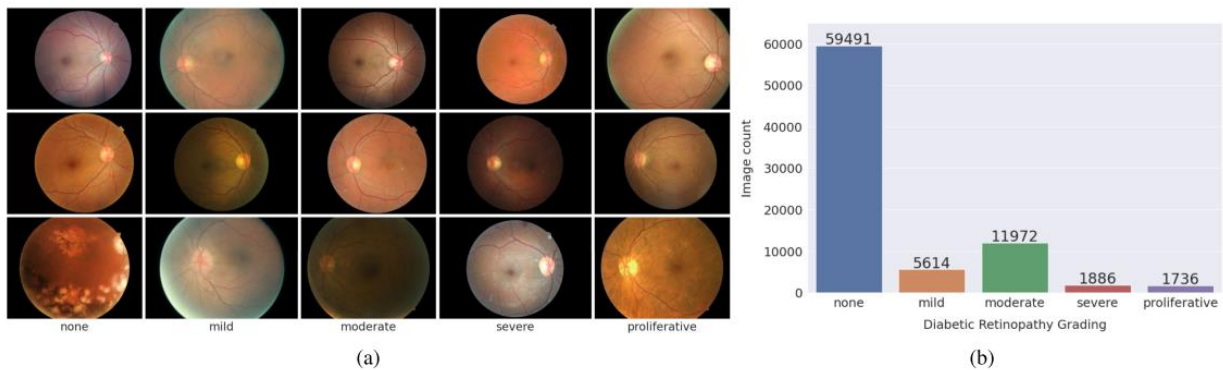


Figure 3: Dataset collection

Few examples from the Eye PACS dataset. Columns in montage (a) show three randomly selected retinal images from each of the five DR grading. The bar chart in (b) shows the distribution of image counts for the five different DR grading in the dataset.

Can be found in [27], [28]. It is important to emphasize that in QBB, DR was not evaluated or graded at all for the participants. So, the participants from QBB may or may not have DR. The dataset is not publicly available in accordance with the Qatar Bio bank data-sharing policy.

The QBB dataset doesn’t contain the same number of images for each participant – there were at most two types of images from the left and right eyes:

- (a) macula-centered images, and
- (b) disc-centered images.

There were 1852 images in total from 492 participants. The mode of the original image sizes was 3696 × 2448 pixels. Figure 1 shows some randomly selected images from the QBB dataset, and the patient counts for each type of retinal image count in the dataset.

This sequence of pre-processing steps transformed each image in our dataset from a varying sized image to a 570 × 570 image with a black background so that all the pre-processed images are aligned with each other and have a similar background. For data augmentation, we applied random horizontal flip, and random brightness and contrast perturbation.

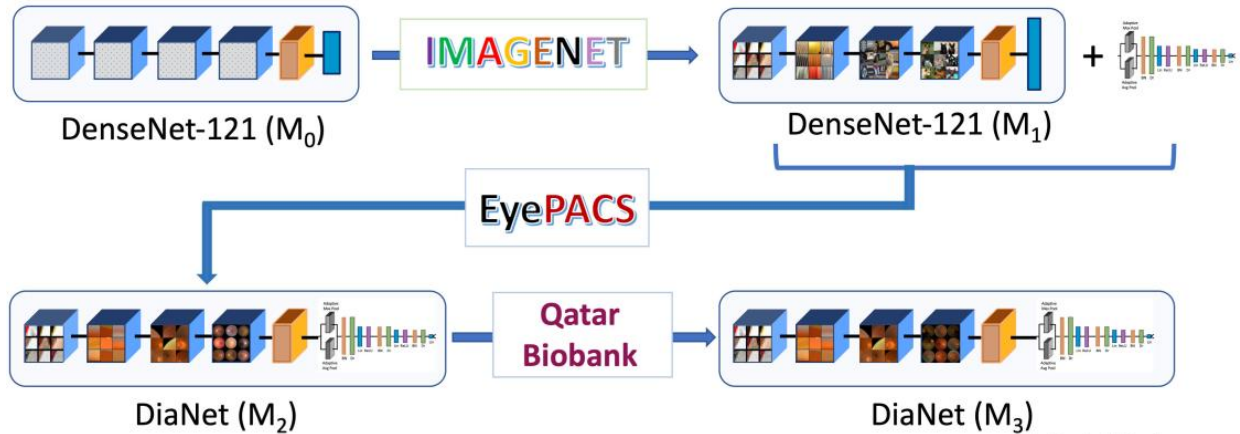


Figure 4: Multi-stage Dia Net

A high-level view of the multi-stage fine-tuning approach for training DiaNet. The top left model (M_0) is a randomly initialized DenseNet-121. Training M_0 on the ImageNet dataset yields M_1 , which is capable of image classification. Adding a few extra layers and fine-tuning it in on the Eye PACS retinal image dataset gives us M_2 ; a model with retinal image understanding capability. Finally, fine-tuning M_2 on the QBB dataset results in our proposed model (M_3) for diabetes detection from retinal images.

To develop DiaNet, we start with a CNN model M_1 that has already been pre-trained on the ImageNet [31] dataset. We then augment the network with a few additional layers before the final layer to increase its ability of understanding more complex patterns from the data. In order to imbue this augmented network with retinal image understanding capabilities, we first fine-tune it on a dataset for the DR detection task, which is defined as the binary task of identifying whether a person has DR or not.

Unlike DiaNet, we considered only the QBB dataset to develop QBB Net. Similar to DiaNet, QBB Net considered DenseNet-121 and ResNet50 for configuring end to-end CNNs and their variants with an XGB as the classifier. We then fine-tuned the models on the QBB dataset only. This results in a total of four additional experimental configurations for QBB Net: QBB Net (with a DiaNet-like architecture), QBBNet_Res50 (ResNet50 backbone instead of a DenseNet121), QBB Net CXGB (XGB classifier on extracted features from QBB Net), and QBBNet_Res50CXGB (ResNet-50 backbone and XGB as the classifier on extracted features from QBB Net).

Model selection, generalization, and performance estimation in the fine-tuning stage on the QBB dataset were carried out using nested cross-validation [38] to prevent data leakage. We used a 5-fold setup in both inner and outer folds. To obtain even more consistent results, we conducted each such experiment n times ($nD5$) and computed the arithmetic mean of the representative metrics for reporting. Due to the enormous size of the Eye PACS dataset, only a single train-validation-test split in the fine-tuning stage using this dataset was sufficient to ensure that these sets have similar distributions.

V. EXPERIMENTAL RESULT

In this project we are detecting presents of diabetes and its stages and to implement this project we are using Convolution Neural Network (CNN) Algorithm). To train CNN we are using IDRID (Indian diabetes Retinopathy Diabetes) images which consists of 5 different types of diabetes disease images. Those 5 types of diseases are Mild, Moderate, No (not resence of diabetes), Proliferative_DR and Severe

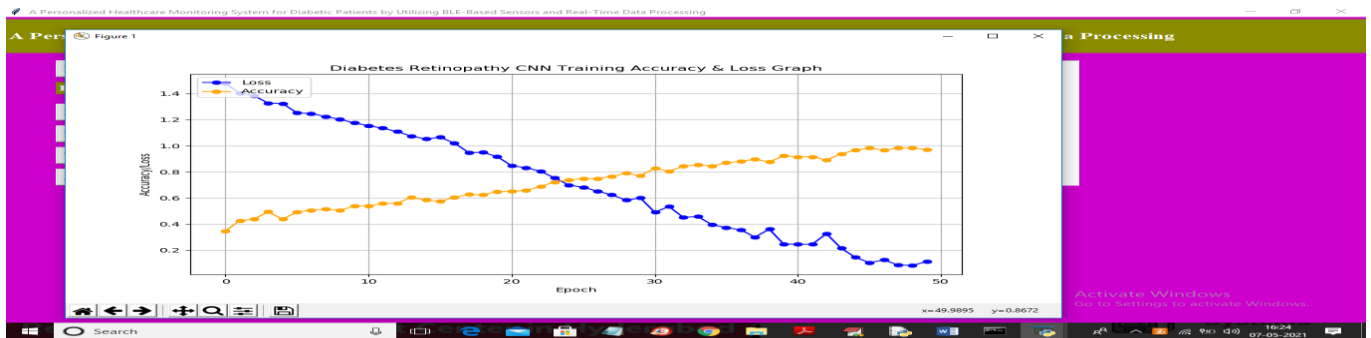


Figure 5: Original image and predicted enhance image

VI. ADVANTAGES AND APPLICATIONS

1. To implement this project we have designed following modules
2. Upload dataset: using this module we will upload diabetes dataset to application
3. Pre-process dataset: using this module we will read all images and then perform preprocessing such as resizing image, rotation and augmentation etc.
4. Train CNN: using this module we will apply CNN algorithm on diabetes dataset to build CNN model to predict disease
5. Upload Test Image & Predict Disease: using this module we will upload retina image and then CNN will predict presence of disease and its stage.
6. The data was pre-processed and augmented using the same approach in multi-stage tuning for DiaNet and single-stage tuning for QBB Net. The Dropout layers we added in our networks used 0.4 as the dropout probability. For minimizing the loss, we used the Adam W optimizer with a One-Cycle Learning Rate Scheduler

VII. CONCLUSION AND FUTURE SCOPE

In this work, we proposed DiaNet, a novel deep learning-based model to distinguish diabetes from the control group using QBB retinal photography. Our model, based on retinal images, achieved over 84% accuracy to classify the diabetes group from the control group achieving a higher level of accuracy than what we achieved using clinical dataset only, for the same purpose. As per our best knowledge, our study is the first, which predicts diabetes considering only retinal images. So, we believe the retinal images can be used in clinical setup to diagnose diabetes and incorporate more images the model could perform at a higher level than what we achieved.

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